AI and ML Model for Fault Identification of Electrical Drives

Synopsis

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Submitted by

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Introduction

In order to reduce costs and conserve energy in industries, induction motor maintenance and condition monitoring are crucial [RAS 23, PRA 17]. Early and precise machine fault detection is essential for preventative maintenance to avoid mishaps that could be disastrous for the user [RAS 23, ARI 11, SHR 17]. Costly periodic fault inspection procedures may be safely simplified or eliminated with the use of automated machinery fault monitoring techniques [VEN 97].

Complex motor theories and structures make it challenging to comprehend electric motors and their uses, particularly in induction motors where the power supply's electrical frequency differs from the motor's actual speed [40]. Sound analysis can also be used to estimate speed. An array of microphones and algorithms to detect various sound emission sources that would help us to measure the speed in many machines with a single device in industries [THY 18].

A machine learning fault diagnostic system must take into account the following factors in order to be successful: (i) a sufficient number of observations for every condition, (ii) effective pre-processing methods, and (iii) the right features extraction algorithm and its application to provide a diagnosis system with high accuracy [RAS 23].

The induction motor is a popular industrial motor due to its many advantages, including its robustness, compact size, and cost-effective operation. It is used in various applications, including pumps, fans, blowers, oil extraction mills, cranes, hoists, lifts, and lathe machines. Failure of this drive could have an impact on output, labour usage, and eventually financial loss [DKC 14, DKC 20, FAB 20]. Vibration and sound analysis are used in induction motor condition monitoring to reliably identify electrical issues in motors [MIK 11]. As per the different survey, bearing faults are the most occurring faults about 41% (EPRI Survey Report) and 42% (IEEE Survey Report) in AC machines in Industries [SIN 03].

In electrical faults, about 30–40% of all induction motor failures are caused by short turns (stator windings). It is widely accepted that insulation failures in multiple turns of the stator coil during a single phase cause a significant amount of stator winding-related problems. The stator inter-turn [SHA 18] defect is the name given to this kind of failure. A stator short-circuit issue arises when the stator windings are shorted. They are categorized as a short circuit between the two turns, two coils, two phases, line to ground, and winding and stator core [SUB 18].

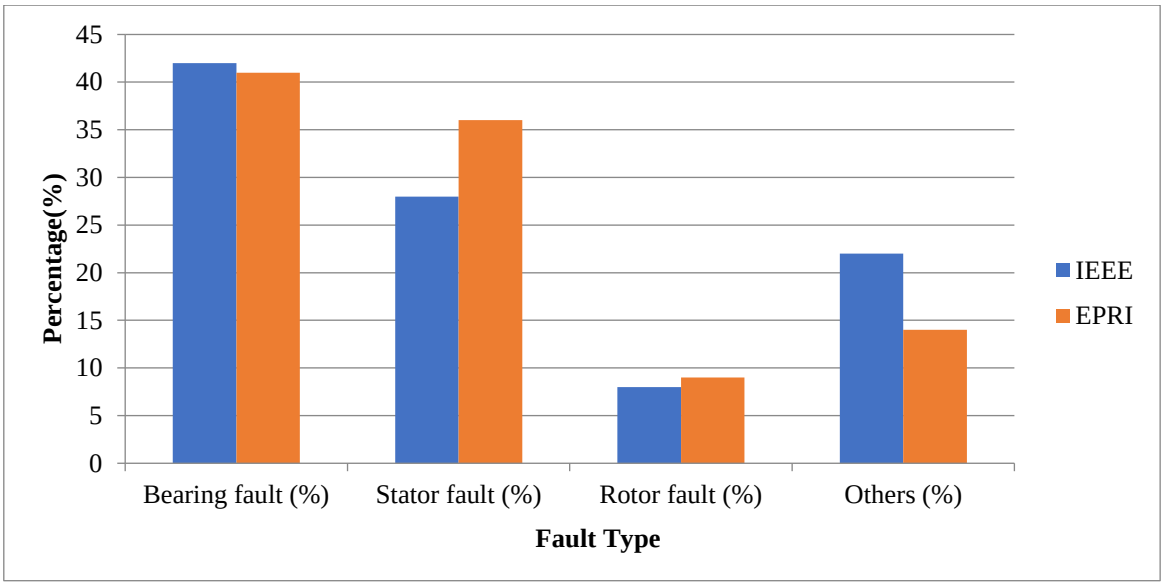

Fig. 1 Comparision of EPRI and IEEE survey [SIN 03]

The two common fault categories that can be monitored by acoustic analysis techniques are mechanical faults, such as cracks in the rotor cage bars and formal deficiencies in the rotational elements.

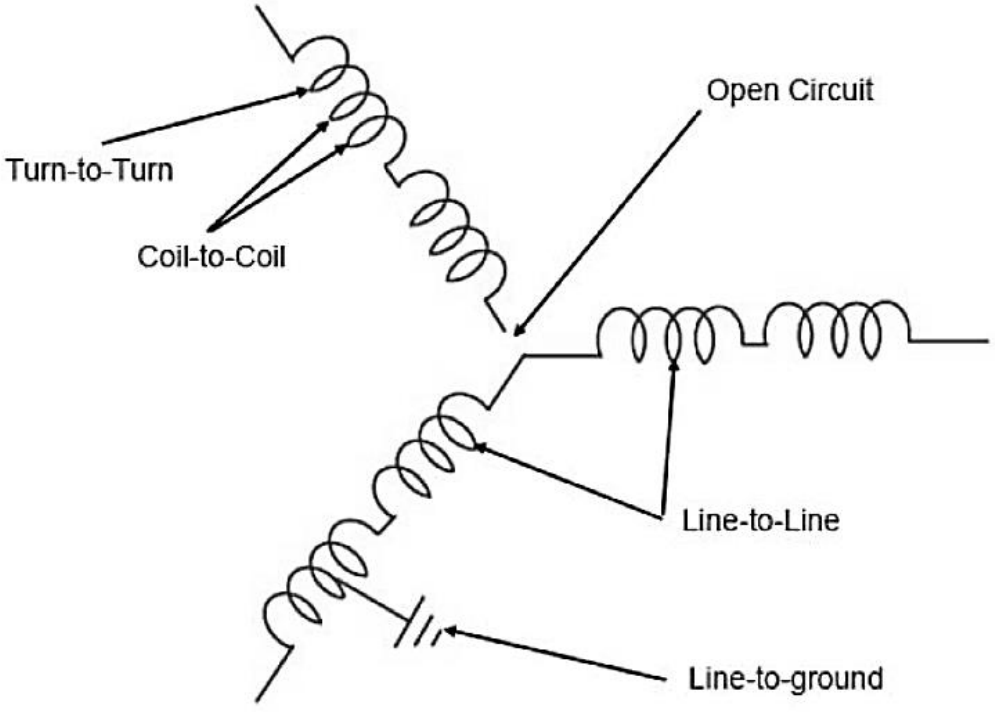

Fig. 2 Stator Faults [RAJ 13]

The most common fault type in the sector is the defective bearing fault [EMI 13]. Most machine faults are caused by mechanical imbalances and bearing issues, particularly in small to medium-sized machines. The electrical supply and the mechanical frequency of bearing failures determine the predictable frequencies at which stator current components are produced [ALB 08].

An uneven air gap between the stator and rotor is known as air gap eccentricity, and it is a typical rotor problem. Excessive eccentricity of the air gap can cause an imbalanced magnetic pull and ultimately rotor-to-stator friction, which causes the machine to vibrate and emit noise. Three type of eccentricity such as static eccentricity, dynamic eccentricity and mixed eccentricity.

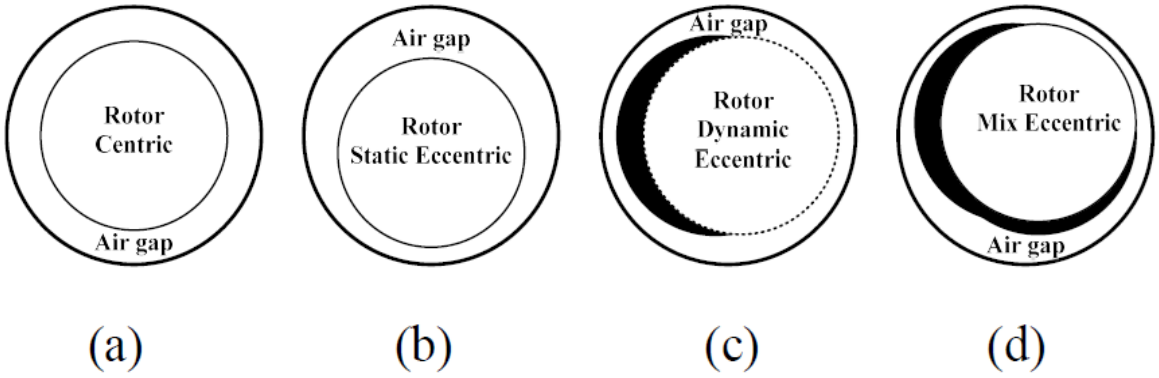

Fig. 3 Types of eccentricity, (a) Rotor Centric, (b) Static, (c) Dynamic, (d) Mixed [PRA 17]

Incorrect rotor position and asymmetrical air gap shape are known as static eccentricity. Dynamic eccentricity occurs due to bearing wear, shaft bending, or mechanical resonances. The combination of static and dynamic is a mixed eccentricity.

Nearly every problem results in air gap torque harmonics with a unique frequency. Various air gap eccentricities exhibit rising odd harmonics, which affect efficiency and power loss detected through vibration, noise, and acoustic sound [PRA 17].

The fault in electrical drives can be found using the MCSA, sound analysis, and vibration analysis methods because of the fluctuating load. This prevents machinery from breaking down permanently. The machine's overall lifespan will be extended by its monitoring [ELD 22].

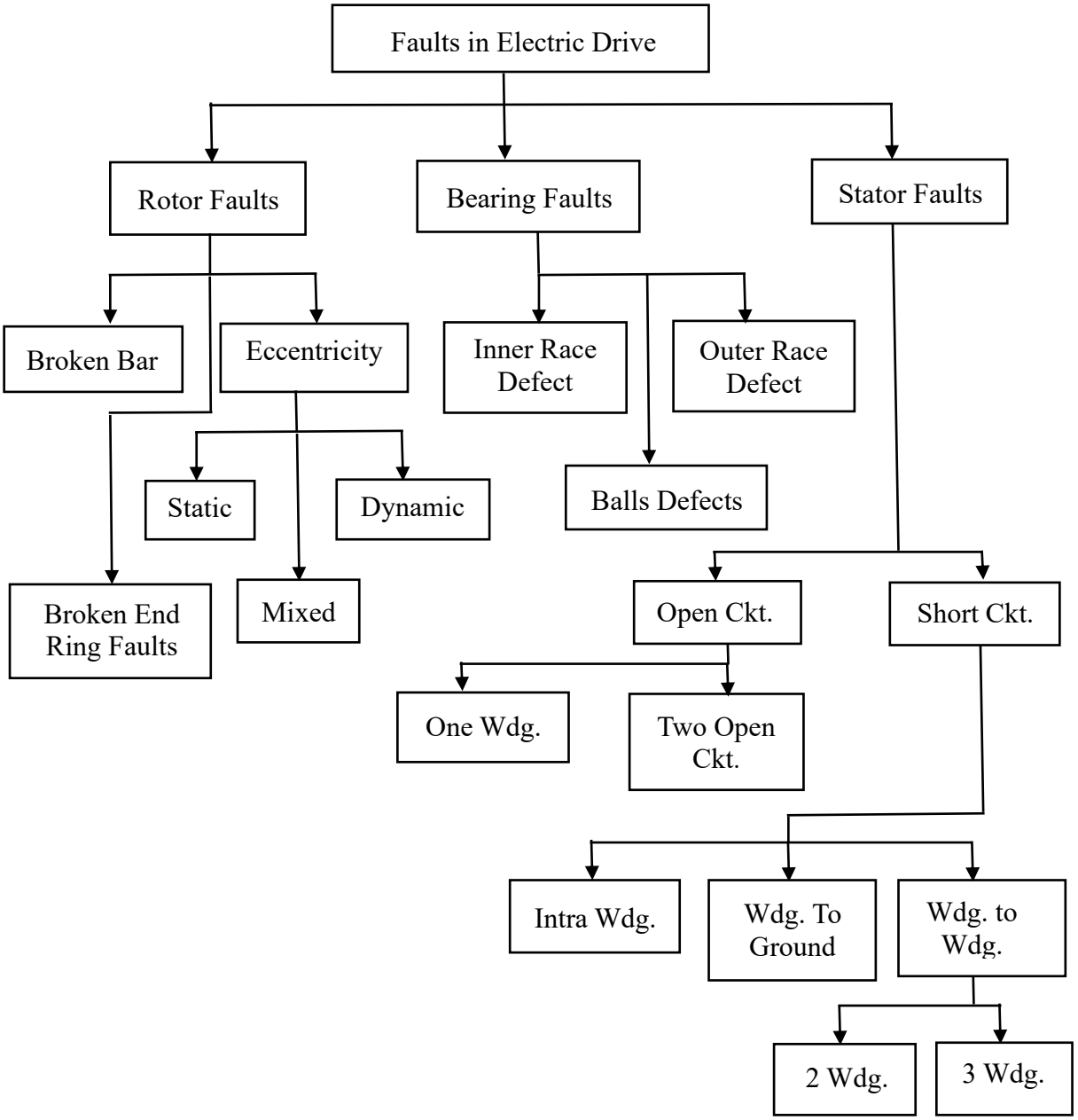

Fig. 4 Electric Drive Faults

Literature Review

The sound that the healthy machine makes while operating differs greatly from that of the unhealthy machine [FIN 90]. It might be challenging to measure the sound level of a fully loaded motor when the surrounding noise is louder than the motor. It is feasible to understand the related frequencies and estimating the source. G. T. Venkatesan et. al. proposed a method for automatically checking faults in helicopter rotor components by sensing acoustic emissions has been introduced. A signal model that is appropriate has been suggested. Since complex component geometry and machine structure may be involved, effort has been taken to assume minimum prior knowledge of the properties in these models

[VEN 97]. Three rotating components i.e. the bearing, fan, and gear can have their faults, diagnosed by utilizing ML algorithms to detect acoustic emission (AE). Rashad et. al mention a variety of ML techniques are employed in various configurations during the development phase [RAS 23].

Rotating machine failures typically arise at the gearboxes and bearings. For a number of decades, envelope analysis was researched and proposed as a means of detecting bearing faults. PR is determined by taking the overall RMS and the harmonics of the fault frequencies, hence lowering the noise level is necessary to obtain the precise PR value. In order to lower the noise level in AE signals, the DWT was included into envelope analysis in this work [KIM 09]. D. Arifianto evaluates the time, frequency and multistage ICA methods for remote condition monitoring through machine sound analysis. Author purposefully inserted balance, misalignment, and bearing faults into electrical water pumps that were otherwise in good working condition. Concurrently, these devices recorded baseline data in an anechoic laboratory and replicated real plant conditions in an open area [ARI 11]. As mentioned, an induction motor's sound or vibration signature, current signature, and other inputs can be applied to detect various machine faultss. The health of the motor is predicted by analyzing these input patterns using a variety of soft computing approaches [DKC 14]. The vibration signal's frequency analysis has been widely used to identify system flaws. One non-invasive method for effectively monitoring an electric motor's condition is MCSA [ELD 22].

Ronnie J. M. Belmans et. al. provides the analysis of audible noise caused by the harmonic of the current and voltage component can be done using the Maxwell stress theorem and with the rotating field theory. When a natural frequency of the stator coincides with one of the frequencies of the electromagnetically stimulated forces, high noise levels may result [RON 87]. Air circulation in a large industrial facility is provided by the fans in a heating system. Magnetic field distortion is the main issue with a single-phase induction motor. The noise generated is not correlated with the current distortion. At low speeds, the noise level was significantly higher than at speeds around the nominal speed. Noise may be produced by poorly designed of both auxiliary and main windings [LEO 15]. A very effective and practical method for identifying mechanical and electromagnetic issues with motors is vibration analysis. These issues include winding degradation, mechanical imbalance, bearing failure, structural resonance and foundation issues, and distortion of the voltage waveform. Theoretically, electromagnetic excitation

forces are briefly examined using the theory of classical electrical machinery [MIK 11].

Stress analysis of induction motor can be done by using sound, vibration and other methods. The electrical variables and sound signal of machine is recorded under different operating conditions using a VIF meter and microphone device. The shape obtain is symmetrical in healthy motor but not symmetrical under different loading conditions. Mathematical modelling is done to understand about the variation in sound signal. Operating conditions are calculated by solving the area below the curve [DKC 20]. An approach for cross-power spectral density estimation from sound measurements (using a microphone) is used to solve the fault detection problem for induction motors. Each failure of a motor has its own design in the acoustic spectrum. The defects on the outer or inner surface result in distinct sideband frequency components. Induction motor faults diagnosis processes can readily incorporate the estimating methodology [EMI 13]. Supachai Prainetr et. al. employed Fast Fourier application to evaluate the fault harmonic signal and noise induced by eccentricity, current and sound signal. The efficiency and power loss are affected by the acoustic sound, vibration, and odd harmonics that are increased by varying air gap eccentricity levels. An induction motor's harmonic current indication may be helpful in identifying its problems [PRA 17].

Additionally, the method of estimating speed via sound analysis was carried out by identifying the FFT peak with the largest amplitude without involving motor functioning. Sound signals are acquired and processed by the embedded system, which is made up of a microcontroller and processing board [THY 18]. Numerous writers have already examined the electromagnetically generated noise of induction motors powered by sinusoidal supplies. Sharad S. Dhamal et. al. discusses the performance of MATLAB simulation on inter-turn short circuit circumstances and balanced supply settings. The stator core and coils would sustain less damage later on if an interturn short circuit issue was detected early on when the motor was operating, reducing maintenance costs [SHA 18]. One of the main ways to increase driving comfort in the automotive industry is to reduce noise and vibration A control method based on SVPWM was used to regulate the phase voltages of a single three-phase induction motor in order to do an examination of vibration and acoustic noise [FAB 20].

The modelling of induction motors under bearing fault conditions is a major area of interest for this work. Any localized bearing fault that produces non-uniformity in the air gap can be considered an

eccentric fault. The stator inductance and, consequently, the stator currents are impacted by this irregular air gap [ARN 20]. A small number of publications analyze the impacts of load and electromagnetic torque while examining the impact of rolling element flaws on the stator current using Hilbert transformation. Only problems with very low critical frequency rates can benefit from bearing fault detection due to the unique properties of vibration and current. Bearing faults can only be reliably detected by a current signal under specific operating conditions [ALB 08]. To identify single-phasing faults in three-phase induction motors, acoustic sound signal analysis is also performed. This article uses signal analysis based on the RMS parameter to compare a healthy and a defective motor in the time-domain, and the FFT with the Average power parameter is used in the frequency-domain [ALI 20].

1. Different Techniques

The fault diagnosis was done by various technique such as fuzzy logic, ANN, artificial neuro-fuzzy inference system and genetic algorithm.

One of the methods for vibration analysis-based motor health monitoring is the fuzzy logic interference system. A fuzzy-logic controller is used to create and implement a simulation model for an induction motor in MATLAB [SHR 17]. The performance of the motor is analyzed using the same technique for short circuit, open circuit, and overvoltage, which is simulated using dynamic equations [SAT 17]. Fault severity can be examined by varying the supply voltage for under voltage and unbalanced fault conditions. The fuzzy fault identification algorithm has been utilized to identify the type of fault using the simulation results [KUM 11].

Stator winding faults can also be determined on monitoring the line/terminal current amplitudes by using fuzzy logic. Stator current amplitudes are described using fuzzy subsets and their associated membership functions. Fuzzy inference is supported by a knowledge base that consists of rule and data bases [HAM 13]. Since fuzzy logic doesn't require a mathematical model, it's a useful detection technique. The MATLAB environment has been used to implement the suggested motor protection system. There had been a comparison of the current amplitudes [ABD 18]. Fuzzy Logic Controllers are also used to identify motor short-circuit faults by monitoring variations in the motor's stator current [SUB 18]. Y. B. Ivonne et. al. discusses the stator problem detection for induction machines using a Neural-Fuzzy approach. Park patterns computations has been done after measuring stator current. Results from simulations had

been shown for the detection of motor faults [IVO 05]. K. Gowthami et. al. provides fault classification of rolling bearings using ANFIS. Feature mining and fault categorization are the two primary sections of this research. MATLAB is used to evaluate a signal's statistical properties. The acquired samples are fed into a neural network for validation, testing, and training. ANFIS receives the statistical information as input for fault categorization [KAL 19]. ANFIS is also used to analyze vibration data from a malfunctioning induction motor in order to create an intelligent fault diagnosis system. The signal spectra of each motor fault model are first acquired. Then frequency spectra are found, and a relationship between the various forms of motor faults and their related spectra is formed. [MAH 17].

Hong Hee Lee et. al. presents a method for utilizing SVM and GA to diagnose mechanical issues. The vibration time signals are used to extract features, which are then chosen using GA with a distance evaluation fitness function. The same GA also simultaneously obtains all SVM parameters. The radial basis function and the polynomial function are the two kinds of kernel functions used to study the SVM [NGO 08]. The use of motor current spectral analysis for the identification and localization of anomalous electrical and mechanical conditions that suggest or could cause an induction motor failure is discussed in this research work. The stator current's spectral analysis data are used in this method. The associated frequencies are identified and the implications of the stator current spectrum are explained. High-resolution spectral analysis of stator current is highly sensitive to induction motor malfunctions that alter key spectral components, including voltage imbalance and single-phasing effects [MOH 99]. Jaewon Choi et. al. presents a framework for induction motor fault diagnosis and severity evaluation based on models. The EKF approach calculates and adjusts the model's parameters to find errors. Modifications to the model's parameters identify system flaws and degradation. The Channel capacity technique, based on Shannon's information theory, is used to quantify the severity of faults. The results imply that model-based diagnostics can identify stator winding issues and damaged rotor bars [JAE 11].

2. Deep Learning Techniques

Neural network-based techniques have also been employed to induction motor fault diagnostics. Real-time fault diagnosis could be facilitated by this algorithm since they can extract adaptive features from raw data without requiring any prior knowledge of fault characteristic frequencies or operating conditions [YAN 20]. The broken bar number of an inductor motor is diagnosed using a neural network

technique. The working status parameters are used to directly diagnose the inductor motor's broken bar number [QIN 07].

Tawee Utthiyuung et. al. mention two neural network algorithms i.e. supervised and unsupervised which are presented with applications to the diagnosis and detection of induction motor faults. According to simulation results, after training the neural network, the system was able to recognize the current spectrum produced by the broken machine. The supervised NN can only identify the malfunctioning machine, it cannot identify the kind of malfunction. On the other hand, the unsupervised neural network can identify the kind of problem by utilizing the sideband component's magnitude [SUT 02]. The vibration signals have been transformed using FFT from the time domain to the frequency domain. The vibration signal's high frequency components were removed using the envelope approach. Only informative features are chosen throughout the features selection process by using the distance evaluation technique. The sensitivity analysis of IMB is introduced to increase the flexibility of the ANN model [TAK 08].

Neuro fuzzy technique is used to diagnostic electrical faults. The stator current's wavelet packet decomposition is used to extract new features with various frequency resolutions. A neuro-fuzzy inference system uses features with varying frequency resolutions as input sets, together with the induction motor's slip speed. Two frequent electrical problems are taken into consideration: air gap eccentricity and rotor bar fracture [ZHO 01].

The use of ML methods for fault diagnosis has grown in acceptance over time. Feature descriptors are derived from the raw signals using deep learning, a feature representation-based technique that offers up new possibilities. P. Chattopadhyay et. al. employs new semi 2D Convolution Neural Networks to detect motor faults, utilizing the advantages of deep learning [CHA 18]. N. Enshaei et. al. suggests a deep learning-based approach for diagnosing bearing problems in induction machines using actual data sets. The suggested model's efficacy is illustrated by contrasting it with a newly created deep neural network (DNN) that takes temporal coherence into account for the same dataset [ENS 19]. The need for induction motor status monitoring is steadily growing, and any malfunction must be regarded as a serious problem since it keeps the motor from malfunctioning and breaking down. This paper is driven by the practical occurrence of a fault, specifically the scratch on the bearing's outer raceway. An online

bearing diagnosis technique based on deep learning (DL) is suggested. Initially, fault characterisation was accomplished using a Convolutional Neural Network (CNN) architecture. The CNN algorithm is trained by first performing a quick Fourier transform analysis utilizing the stator's load current, and then extracting features from certain frequency components [MIZ 18].

ANN are used for sensor less control of drives. In order to simulate an induction motor, which delivers the drive's actual speed directly, a feedforward ANN with a single hidden layer was created and trained offline. Subsequently, the model was integrated into the field-oriented control system, completely replacing an incremental encoder. An experimental drive with an induction machine and a controlled digital signal controller was used to evaluate the suggested method. The findings demonstrate excellent precision in the low-speed range [PAL 20]. Peng Wang et. al. develops a deep learning method based on deep belief networks (DBN) to characterize the operating state by learning features from the frequency distribution of vibration signals. To achieve automatic and intelligent problem diagnosis, it combines the classification task with the feature extraction technique. A layer-by-layer pre-training approach is used to train the DBN model, which is constructed by stacking several restricted Boltzmann machine (RBM) units [WAN 17].

3. Machine Learning and Artificial Intelligence

The diagnostic approach locates and detects the switch under an open-circuit failure by utilizing both ML and signal processing approaches. Each phase current signal is first subjected to the Hilbert-Huang transform using the empirical ensemble mode decomposition. Two parameters, namely the correlation coefficient and the root mean square, are computed for each function in order to select the one that best indicates the open-circuit fault harmonic. The fault harmonic of the switch can be extracted from the spectral envelope of the optimum function [CHE 22]. Induction motor problems must be fixed promptly to prevent losses. Applications of ML algorithms in the fault detection sector offer a dependable and efficient preventive maintenance solution [PRA 21].

Induction motors (IM) with high torque and power factors are difficult to design, which has made EV applications less successful. Hence, the work is diagnosing faults in the planned IM under varied load conditions. A fault detection strategy is implemented with various ML techniques like Support Vector Machine (SVM), K-nearest neighbours (k-NN), ML perceptron (MLP), Random Forest (RF), Decision

Tree (DT), Gradient boosting (GB), Extreme Gradient Boosting (XGBoost), and Deep Learning (DL) for both healthy and faulty conditions. Short Circuit (SC), High Resistance connection (HRC), and Open-Phase circuit (OPC) are considered as faulty states for this study. ML evaluates motor performance under varying loads in both healthy and defective conditions [AIS 23]. A fault detection method utilizing sound signals has been suggested in this study. Sound sensors (microphones) are less expensive than other kinds of sensors, and they can detect sound signals without making direct contact with the motor or stopping it. Mel-frequency cepstral coefficients (MFCCs), Wavelet scattering, ensemble learning, and convolutional neural network (CNN) classification techniques are all hybridized. The efficiency of the suggested approach was demonstrated by comparing it to the most advanced techniques using a standard database [SHI 24].

T. Ramesh et. al. uses the AI-based speed control loop (SCL) to directly control the torque and flux of the induction motor drive (lMD) in order to improve the speed response in both steady state and transient situations and reduce the ripple contents of the stator current, flux, and electromagnetic torque. The induction motor's nonlinear model makes it challenging to optimize the high performance of the DTC of IMD using the traditional (PI controller) scheme. Consequently, PIFLC and fuzzy logic controller (FLC) strategies are suggested to enhance system performance. MATLAB/Simulink software is used to display the thorough simulation results in forward motoring under no-load, load, and abrupt change in speed situations in order to support the viability of the control approach [RAM 13].

IMD performance and operation are enhanced by the use of AI technology, specifically neural networks. In this paper, a neural controller is used to simulate dynamically. Simulation results across conventional, fuzzy, and neural network controllers (NNW) using the integrated environment are compared. The traditional proportional integral controller's performance is contrasted with that of controllers based on fuzzy logic and ANN. MATLAB/SIMULINK is used for the dynamic modeling and simulation of induction motors, and the AI controller's dynamic performance has been examined [MEN 14]. H. Abu-Rub et. al. presents an AI-based sensor-less vector control system for an induction motor. They includes discussion of the fuzzy logic and ANN solutions. The speed controller uses a feed forward ANN with one input, two hidden layer units, and one output. By modifying the network's new weights in accordance with the discrepancy between the command and actual speeds, the rotor speed may be

tracked. The proposed controller and the traditional PI are compared in this study. The rotor speed follows the instruction one quickly and smoothly, with very little steady state error and no overshoot [ABU 07].

E. V. Morozova et. al. uses an induction motor with a frequency changer as an example of an AI-based control system. A fuzzy output controller is used to implement management [MOR 20]. An analysis of cutting-edge techniques used for induction machine control is presented. The purpose of the work is to compare the traditional controller with more sophisticated control methods like ANN and fuzzy logic. The outcomes of numerous simulation tests demonstrate the resilience characteristics of the various control schemes depending on the rotor flux orientation [MED 17].

In order to continuously monitor the induction motor, recent work has applied a micro-controlled sigma-delta converter to build a non-invasive fault detection method based on the information provided by the harmonics content of the external magnetic field. Signal sampling has the benefit of not requiring analog filters between the microcontroller and the transducer [GAR 23]. Sasireka M. et. al. use a support vector machine (SVM) for classification and LabView for signal processing and data collection. The existing motor control systems in the research work can be easily integrated which doesn't require any further sensors or hardware [SAS 23]. T. G. Amaral et. al. identify drive faults by analyzing startup currents using the S-Transform and identifying distinctive patterns [AMA 24]. A number of ML models are applied to the machine model in order to test the robustness of the fault identifying and diagnosis process, with the Random Forest algorithm demonstrating the best performance. The Park's transformation is used to model the defective induction motor by changing it from a phase to a two-phase system in order to collect the defective dataset [TUR 24].

In the presence of an unbalanced supply voltage, the researcher is visualizing the changes and variations in electrical and mechanical quantities when the machine is impacted by broken rotor bar faults. The suggested approach mainly relies on FFT-based signal spectral analysis of stator current [MER 24]. Eccentricity, broken rotor bars, and bearing faults are among the fault types covered by another author, who also discusses methods including MCSA, partial discharge testing, and AI-based methodologies [BAH 24]. A technique for accurately diagnosing induction motor problems that uses acoustic emission signal processing retrieved from spectrogram datasets. Three deep learning models i.e. the Feed-

Forward Neural Network (FFNN), Convolutional Neural Network (CNN), and Residual Network (ResNet) are used to detect electric drive faults [MUJ 24].

ELSE-RNN is utilized to improve the performance of fuzzy-tuned proportional-integral (PI) supervision and supercapacitor (SC) storage technology. Signal processing methods like the Hilbert transform are used to detect stator, rotor, winding, and bearing faults. The ELSE–RNN technique simplifying the process of identifying and categorizing errors using a verified system. MATLAB is used to implement the ELSE–RNN approach [BAL 24]. The sinusoidal waveforms of the different fault states were used to extract the training dataset. The data is given to the classification learner app in MATLAB for learning. The best learning algorithm in terms of prediction time is determined by training various SVM learning algorithms [ZIT 23]. The benefits and drawbacks of monitoring signals are critically examined using the cutting-edge technology in fault detection such as ML and signal processing techniques [RUZ 24].

Research Gap

- The multiple signatures (like sound, current, temperature etc.) can be analyzed using soft computing techniques for accurate fault identification [DKC 14].
- The study might be extended to include other operating circumstances and various faults, such bearing or short circuit issues [DKC 20].
- The system can be used to analyze and avoid bearing and bearing support failures in an industrial setting that rotates continuously under typical operating conditions [THY 18].
- The work can be expanded to use a fuzzy logic algorithm or any other diagnostic technique to detect and examine an induction motor's rotor fault [KUM 11].

Problem Statement

To detect faults in electric drives using multiple signatures under various operating situations and analyze them using Artificial Intelligence and Machine Learning.

Hypothesis

The electric drives such as induction motor are creating multiple signatures while running. The various signature patterns of the motor under normal and abnormal conditions are different, which can be detected by visualising patterns to prevent downtime of a machine.

Objectives

1. To design and develop hardware and software for multiple signature acquisition.
2. To acquire multiple signatures under healthy and various unhealthy conditions of electric drives such as induction motor.
3. To analyze these signatures for identification of healthy conditions and type of faults.
4. To design and development of AI and ML model for fault identification.

Methodology

In the beginning, the literature survey of the report can be done by studying the national and international journals, research and review paper. This must be achieved to know about the present state of art in this area. In next phase, multiple signatures under different operating conditions of motor will be recorded i.e. healthy and by creating fault (i.e. mechanical fault such as bearing fault, cooling fan fault and electrical fault such as open circuit/short circuit faults) in motor in order to achieve the other step where fault detection is done to analyze the different pattern.

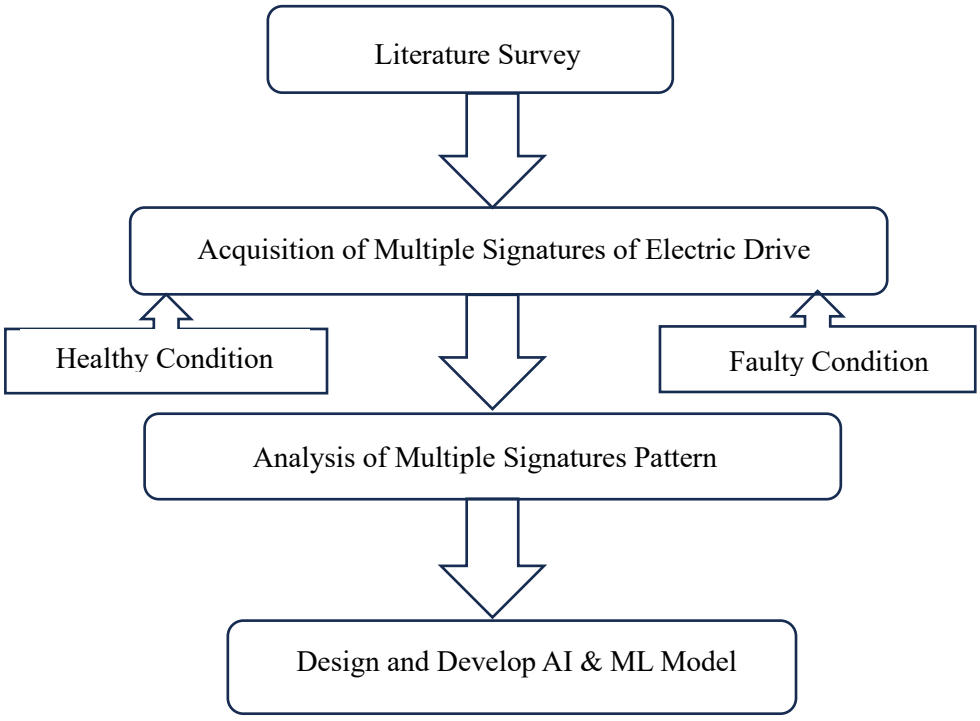
Literature Survey
Acquisition of Multiple Signatures of Electric Drive
Healthy Condition
Faulty Condition
Analysis of Multiple Signatures Pattern
Design and Develop AI & ML Model

Fig.5 Flowchart

After analyzing the patterns to detect faults by comparing from a healthy condition an AI model is design and developed in order to save costs and conserve energy in industries.

Potential Application

The potential application of the work of detecting pattern of faults in a widely used motor by visualizing. Such faults detection technique can save lot of money and labour cost during the downtime of motor. Further, in industries this technique can help in detecting faults both the parameters by listening and visualizing.

Conclusion

In order to prevent total failure, industries must diagnose induction motor problems at early stage. On comparing the healthy and faulty condition in motor, an easy visualization can be created by implementing the tested result using AI. This can prevent the downtime of induction motor in industries and also create a convenient way to recognize the faults.

In the event of a malfunction, the motor can keep operating and lead to major failures in windings, core, bearings etc. An experienced person/expert can detect the fault by listening the sound of electric drives such as induction motor. Therefore, errors can be avoided by keeping an eye on the motor's output and turning it off before the major damage takes place in the motor. Such observation will be done when there is an AI model which can help us in simply visualizing the faults.

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